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FUNCTIONAL PROPERTIES OF FEED-FORWARD INHIBITION

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ABSTRACT
Neurons receive a large number of excitatory and inhibitory synaptic inputs whose temporal interplay determines the spiking behavior. On average, excitation and inhibition balance each other, such that spikes are elicited by fluctuations [1]. In addition, it has been shown in vivo that excitation and inhibition are correlated, with inhibition lagging excitation only by few milliseconds (∼6 ms), creating a small temporal integration window [2, 3, 4]. This correlation structure could be induced by feed-forward inhibition (FFI), which has been shown to be present at many sites in the central nervous system.
To characterize the functional properties of feed-forward inhibition, we constructed a simple circuit using spiking neurons with conductance based synapses and applied spike pulse packets with defined strength and width [5].
We found that the small temporal integration window, induced by the FFI, changes the integrative properties of the neuron. Only transient stimuli could produce a response when the FFI was active, whereas without FFI the neuron responded to both steady and transient stimuli. In addition, the FFI increased the trial-by-trial precision.

KEY WORDS
feed-forward inhibition, precision, conductances, sparseness

Introduction

Neurons receive a large number of excitatory and inhibitory synaptic inputs whose temporal interplay determines the spiking behavior. In vivo measurements have shown that, on average, excitation and inhibition dynamically balance each other [6]. Accepted single neuron models assume this balance [7, 8], and it has been shown that it can exist in cortical network models [1], creating an activity regime that closely resembles cortical spiking activity in vivo.
In addition to the dynamic balance, it has been shown in vivo that excitation and inhibition are correlated, with inhibition lagging excitation only by few milliseconds (∼6 ms) [2, 3, 4]. This correlation structure could be induced by feed-forward inhibition (FFI). Here an excitatory projection directly synapses onto a neuron while inhibition is provided disynaptically by local inhibitory neurons which also receive excitatory inputs from the same projection. This type of connectivity pattern has been shown to be present at many sites in the central nervous system.
To characterize the functional properties of feed-forward inhibition, we constructed a minimal cortical circuit containing the principal elements (shown in Figure 1). We then applied spike pulse packets with defined width and size [5] to investigate how the statistics of the stimulus interact with the circuit, both in the case when FFI was present and in the case it was not.

Method

The cortical circuit contained two major neuron types, the excitatory (regular-spiking, RS) and inhibitory (fast-spiking, FS) neurons. The neurons were modeled as leaky-integrate-and-fire neurons with conductance based synapses. In the circuit we included one RS neuron and a pool of FS neurons. The size of the inhibition pool was set to nFS = 20 when investigating the effect of FFI onto the spiking response of the RS neuron. For the control condition, in which excitation was not accompanied by inhibition, we set nFS = 0. The input to the circuit was a popula-

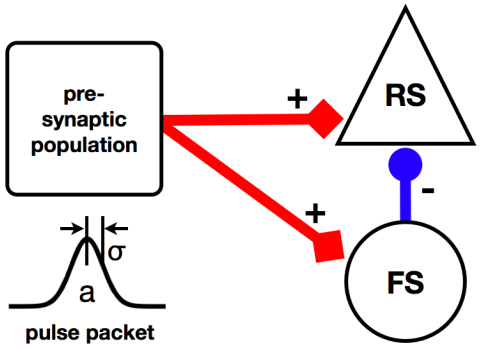

Figure 1. Schematic diagram of the model circuit.

tion of pre-synaptic neurons, whose spiking behavior was drawn from a gaussian distribution, creating a pulse packet [5] with strength (i.e. number of spikes in the packet) a and temporal width σ. Each cortical neuron received 100 randomly chosen synapses from the pre-synaptic population. Due to the limited size of the pre-synaptic population, the cortical neurons received highly similar synaptic inputs [9]). The unitary synaptic strength of the connec-

tion of each FS neuron onto the RS neuron was set to 2 nS. The synapses from the pre-synaptic population onto the RS neuron had a strength of 1 nS, whereas they were tree time stronger onto the FS neurons [10].The delay between the FS neurons and the RS neuron was set to 2 ms [2, 10].
See Figure 1 for a schematic diagram of the model.
The simulation was written in python [11] using pyNN [12] as interface to the NEST simulator [13].

Results

Intracellular measurements

Example traces of the membrane potential and the conductances of the RS neuron, receiving a pulse packet of a = 2 spikes and σ = 10 ms, are shown in Figure 2. In the left column (a,c,d) the FFI is not activated, such that impinging excitation (red trace in c) can be freely integrated to produce multiple spikes. Spikes are shown here as a reset to the resting potential after the membrane potential reached the threshold (green dots in a,b). In this case, the cross-correlation between excitation and inhibition is flat (e). By contrast, with activated FFI, right column (b,d,f), the incoming excitation is quickly quenched by inhibition (blue trace in d), eliciting only one spike (b). Here excitation and inhibition are strongly correlated (f), similar to [3, 4].

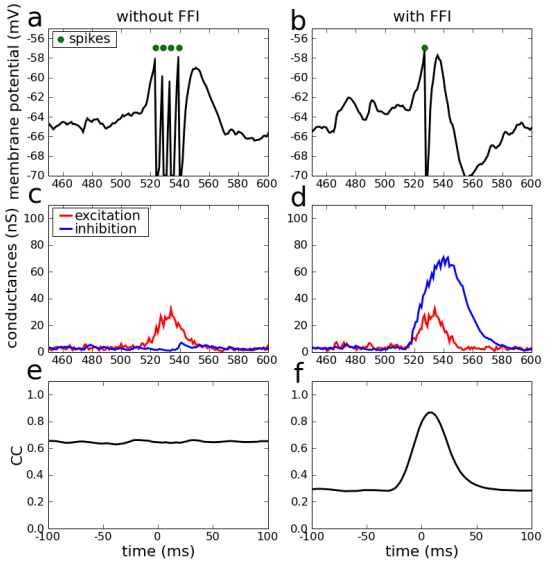

Figure 2. Membrane potentials and conductances.
Shown are example traces of the membrane potentials (a,b), the incoming conductances (c,d) and their cross-correlations (e,f) for the circuit without (left) and with (right) FFI. Details see text.

Spike counts and trial-by-trial precision

To systematically characterize the functional properties of the circuit with and without FFI we varied the parameters σ and a. σ was varied from 2 ms, to mimic transient inputs, till 100 ms to mimic steady inputs. Note that we used a non-linear scale for σ to zoom in on the small-σ regime. The stimulus magnitude was varied by the parameter a, ranging from 1 spike per synapse for weak stimuli to 10 spikes per synapse for strong stimuli. For small σ, a might get unrealistic high, i.e. 10 spikes per synapse within 5 ms is not physiologically realistic, however, our aim was to get an overview of all combinations of σ and a, therefore, we did not exclude such unrealistic combinations. We estimated the spike count per stimulus of the RS neuron to assess the sparseness/denseness of the response. To quantify the trial-by-trial precision of the response we simulated multiple trials and estimated the zero-lag correlation coefficient of the binned spike trains (binwidth 1ms), excluding same trials.

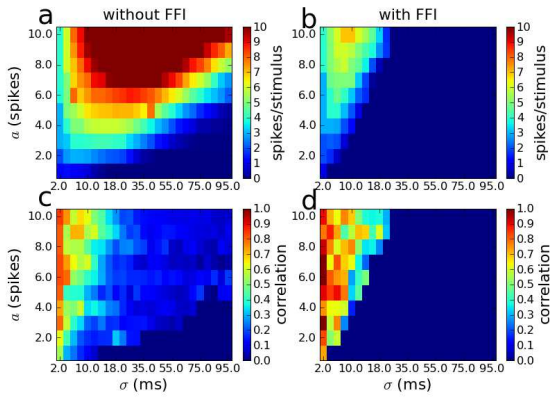

Figure 3. Spike count and precision.
Shown are the spike count per stimulus (a,b) and the trial-by-trial precision (c,d) for the circuit without (left) and with (right) FFI. Details see text.

Figure 3 shows the resulting spike counts and trial-by-trial correlations for all tested σ and a, again, in the left column without FFI and in the right column with FFI.
When stimulated with transient synchronous inputs (pulse packets with $\sigma < 10$ ms), both circuits showed similar responses (a,b). The spike count was sparse, with 1-3 spikes/stimulus for an a, a <4, which was biological realistic for this range of σ. Only for larger a did the response of the circuit without FFI become more dense (top, left area in a), whereas it remained sparse with FFI (b).
When stimulated with more steady inputs (pulse packets with large σ), the effect of the FFI was distinct. Whereas supra-threshold steady inputs elicited dense responses with more then 10 spikes/stimulus without FFI (middle area in a), the responses were suppressed with FFI (b). This non-linear suppression is caused by the lagged inhibition. The time-lag creates a small temporal integration window, en-

abling the RS neuron to act as high-pass filter. Therefore, the responses to transient inputs remained relatively unchanged, whereas the steady ones were suppressed [14] (compare the probability of having sparse or dense responses with or without FFI in Figure 4 a).
By suppressing the responses to steady inputs, the FFI also increased the precision of the response, effectively by reducing multiple spiking, thereby prohibiting later, less precise spikes to occur (compare red and blue curves in Figure 4 b). Whereas transient inputs produced precise responses, steady ones failed to do so [15]. (compare the trial-by-trial correlation for pulse packets with small σ to pulse packets with large σ, Figure 3 c,d).

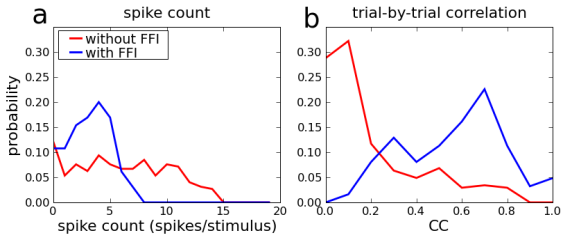

Figure 4. Probability of spike count and precision.
Shown are the probabilities of spike counts and trial-by-trial correlation for the circuit with and without FFI. Details see text.

Conclusion

We characterized the consequences of correlated and lagged inhibition, induced by the feed-forward inhibition scheme (Figure 1,2). In agreement with the literature [14], we found that the small temporal integration window induced by the FFI changes the integrative properties of the RS neuron such that only transient synchronous inputs can produce a response (Figure 3). In addition, by suppressing unprecise responses to steady inputs, the FFI increases the precision of the response (Figure 4). In conclusion, the functional property of the correlated and lagged inhibition, which could be the result of feed-forward inhibition (however, see Fig. 4 in [16] for a similar effect of recurrent inhibition), support the idea that synchrony is important for cortical processing.

Acknowledgments

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References

[1] Arvind Kumar, Sven Schrader, Ad Aertsen, and Stefan Rotter. The high-conductance state of cortical networks. *Neural computation*, 20(1):1–43, Jan 2008.

[2] Michael Wehr and Anthony M Zador. Balanced inhibition underlies tuning and sharpens spike timing in auditory cortex. *Nature*, 426(6965):442–6, Nov 2003.

[3] Michael Okun and Ilan Lampl. Instantaneous correlation of excitation and inhibition during ongoing and sensory-evoked activities. *Nat Neurosci*, 11(5):535–7, May 2008.

[4] Pierre Baudot, Manuel Levy, Olivier Marre, Cyril Monier, and Yves Frégnac. submitted.

[5] Markus Diesmann, M O Gewaltig, and Ad Aertsen. Stable propagation of synchronous spiking in cortical neural networks. *Nature*, 402(6761):529–33, Dec 1999.

[6] Bilal Haider, Alvaro Duque, Andrea R Hasenstaub, and David A McCormick. Neocortical network activity in vivo is generated through a dynamic balance of excitation and inhibition. *J Neurosci*, 26(17):4535–45, Apr 2006.

[7] Frances S Chance, L F Abbott, and Alex D Reyes. Gain modulation from background synaptic input. *Neuron*, 35(4):773–82, Aug 2002.

[8] Michelle Rudolph, Martin Pospischil, Igor Timofeev, and Alain Destexhe. Inhibition determines membrane potential dynamics and controls action potential generation in awake and sleeping cat cortex. *J Neurosci*, 27(20):5280–90, May 2007.

[9] Ilan Lampl, I Reichova, and David Ferster. Synchronous membrane potential fluctuations in neurons of the cat visual cortex. *Neuron*, 22(2):361–74, Feb 1999.

[10] Scott J Cruikshank, Timothy J Lewis, and Barry W Connors. Synaptic basis for intense thalamocortical activation of feedforward inhibitory cells in neocortex. *Nat Neurosci*, 10(4):462–8, Apr 2007.

[11] python. http://www.python.org.

[12] pyNN. http://neuralensemble.org.

[13] NEST. http://www.nest-initiative.org.

[14] David J Pinto, Jed A Hartings, Joshua C Brumberg, and Daniel J Simons. Cortical damping: analysis of thalamocortical response transformations in rodent barrel cortex. *Cereb Cortex*, 13(1):33–44, Jan 2003.

[15] Zachary F Mainen and T J Sejnowski. Reliability of spike timing in neocortical neurons. *Science*, 268(5216):1503–6, Jun 1995.

[16] Arvind Kumar, Stefan Rotter, and Ad Aertsen. Conditions for propagating synchronous spiking and asynchronous firing rates in a cortical network model. *J Neurosci*, 28(20):5268–80, May 2008.